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Daily Random Urinalysis Testing: Consequences of Deterrence Functions

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This is the fifth in a series of reports concerned with developing probability models for the analysis of random urinalysis programs. A Markov daily testing model was developed. The distributions of the time to detection and the number of tests to detection were derived as a function of the daily testing rate and the conditional probability of testing positive. Deterrence functions are defined and examples are given. When the testing rate has no deterrent effect on drug use, the average time to detection decreases with increasing testing rates and the average number of tests to detection remains constant. When the testing rate has a deterrent effect, average time to detection can be minimized. The average number of tests to detection increases with increasing testing rates.

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Foreword

This report was prepared as part of the Statistical Methods for Drug Testing project (Program Element 0305889N, Work Unit 0305889N.R2143DR001), sponsored by the Chief of Naval Personnel (PERS-63). The objective of the project is to develop a unified set of statistical methodologies for the analysis of drug testing programs and data. The work described here was performed during FY94.

This is the fifth in a series of reports concerned with developing probability models for the analysis of random urinalysis programs. The first report is *Probability of Detection of Drug Users by Random Urinalysis in the U.S. Navy* (NPRDC-TN-93-2). The second report is *Markov Chains for Random Urinalysis I: Age-Test Model* (NPRDC-TN-93-5). The third report is *Markov Chains for Random Urinalysis II: Age-Test Model with Absorbing State* (NPRDC-TN-93-6). The fourth report is *Markov Chains for Random Urinalysis III: Daily Model and Drug Kinetics* (NPRDC-TN-94-12).

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Summary

Background

In 1981 the U.S. Navy introduced a *zero tolerance* drug policy, i.e., all service members should be processed for separation for the first drug abuse incident. The cornerstone of this policy is an aggressive random urinalysis testing program. The objectives of this program are to deter and detect drug use, as well as provide data on the prevalence of drug use.

Previous research developed a model for detection based on current Navy practice and an alternative testing algorithm less sensitive to gaming (Thompson & Boyle, 1992). Two other reports described Markov models for analyzing random urinalysis strategies stratified by "time last tested" (Thompson, Boyle, & Hentschel, 1993; Boyle, Hentschel, & Thompson, 1993). Finally, a fourth presented a daily Markov model that included drug excretion rate kinetics (Thompson & Boyle, 1994). This report, unlike the previous work, addresses the relationship between deterrence and random testing rates.

Objective

This report explores the probabilistic consequences of potential deterrent effects of random urinalysis testing rates on drug usage.

Approach

First, daily random urinalysis testing is modeled as a Markov chain. The parameters are the daily testing rate and the conditional probability of a positive test. Distributions of detection time and number of tests to detection are developed. Second, a method for deriving the conditional probability of a positive test is discussed. The method is applied to cocaine excretion kinetics as presented in Thompson and Boyle (1994). Third, deterrence functions are defined. Some examples are given and comparisons made.

Conclusions

A Markov daily testing model was presented with constant daily testing rate and constant conditional probabilty of a positive test. The distributions of time to detection, number of tests to detection, and the corresponding average values were derived. Borrowing results on cocaine excretion kinetics from Thompson and Boyle (1994), the conditional probability of a positive test for cocaine was modeled as a quadratic function of the number of days per week cocaine is used.

A number of deterrence functions were postulated. One extreme case is no deterrence. In this case, the average number of tests to catch a cocaine user is constant and the time to detection decreases with increasing testing rates. At the other extreme (maximum deterrence), drug usage drops to zero days per week for any positive testing

rate. In this case, the number of tests in any time period follows a binomial distribution, just as for a nonuser. For general deterrence functions, the average number of tests to detection increases with increasing testing rates. The average time to detection decreases to a minimum and increases thereafter with increasing testing rates. Policy makers should find this important, since it suggests the possibility of setting testing rates that catch drug abusers in the shortest possible time. Rapid detection should not only minimize the loss in productivity due to illegal drug use but should reduce the chances of costly accidents involving both human lives and expensive hardware.

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Introduction

In 1981 the U.S. Navy introduced a *zero tolerance* drug policy (i.e., all service members should be processed for separation for the first drug abuse incident). The cornerstone of this policy is an aggressive random urinalysis testing program. The objectives of this program are to deter and detect drug use, as well as provide data on the prevalence of drug use. Current policy (Chief of Naval Operations, 1990) directs Navy commands to test 10% to 20% of their members each month. From 1983 to 1991 the proportion of all Navy service members sampled who tested positive for drugs fell from 7% to 1%. Although this suggests the Navy's testing program has been successful, continuing evaluation and improvement of the program is warranted, since drug abuse negatively impacts readiness, health, and safety.

This is the fifth in a series of Navy Personnel Research and Development Center (NAVPERSRANDCEN) reports developing probabilistic models of random urinalysis programs. The first report (Thompson & Boyle, 1992) described a model for detection based on current Navy practice. An alternative testing algorithm was proposed which is less sensitive to gaming. Software implementing this algorithm has been developed and is currently undergoing test and evaluation in several fleet units and shore activities. The second and third reports (Thompson, Boyle, & Hentschel, 1993; Boyle, Hentschel, & Thompson, 1993) introduced Markov models for analyzing age-test strategies as proposed by the Nuclear Regulatory Commission (1988). That is, the probability of a person being tested depends on the amount of time since the person was last tested. The fourth report (Thompson & Boyle, 1994) is an extension of the first report and quantifies the effects of daily variations in testing rates on detection of drug users. It presents a daily Markov model that includes cocaine excretion rate kinetics. It shows that unequal daily testing rates provide dramatic opportunities for gaming drug users to extend the mean time to detection. Gaming is not possible with equal probabilities of testing across days. The Drug Policy Analysis System (DPAS) has been devloped by NAVPERSRANDCEN incorporating the work in these four reports. DPAS is a PC-based software product that allows commands to quantify trade-offs among costs, testing rates, and the probability of detecting a drug user.

While this earlier work quantifies the relationships among detection, gaming, and random urinalysis strategies, the relationship between deterrence and random testing rates has not been addressed. At one extreme, imagine an "irrational" drug user who uses drugs 3 days per week, independent of the testing rate. This individual's usage pattern is not impacted by a random testing program and is clearly not deterred by random testing. At the other extreme, a completely "rational" user might curtail all usage once informed that he or she is being tested, no matter what the level. Presumably, the majority of drug users fall somewhere between these two extremes. The objective of this report is to explore the consequences of potential deterrent effects of random testing rates.

The report defines a Markov model where the daily testing rate and the conditional probability of a positive test, given the individual is tested, are constant. This latter probability is defined for a cocaine user who uses any specified number of days per week. Examples of deterrence functions are given and the consequnces analyzed. The last section of the report offers a number of conclusions.

A Markov Testing Model

Using the theory and notation developed in previous reports (Thompson et al., 1993; Boyle et al., 1993; Thompson & Boyle, 1994), a class of Markov chains with transition matrices P of the following form can be defined:

$$P = \begin{bmatrix} p(1-\alpha) & 1-p & \alpha p \\ p(1-\alpha) & 1-p & \alpha p \\ 0 & 0 & 1 \end{bmatrix}. \tag{1}$$

The chain defined by Equation 1 represents the simplest daily testing set-up where the probability p of an individual being tested and the conditional probability α of a positive result, given the individual is tested, are the same each day. An individual is in state 1, associated with row 1 and column 1 of P, if tested negative yesterday, and in state 2, associated with row 2 and column 2, if not tested yesterday. State 3, last row and last column, is the detected state. An individual enters state 3 upon testing positive, and remains in this state for all time. When $\alpha, p > 0$, individuals must be caught or detected in finite time. Assume the process starts in state 1.

The relevant random quantities associated with the above process are defined as follows:

N_1 = number of negative tests before detection (including the initial negative test but not including the final positive test).

N_2 = number of days not tested before detection.

T = detection time where $T \geq 1$.

Clearly, $T = N_1 + N_2$, and we wish to determine the distributions of these random quantities. To this end, we cite concepts and notation from Hoel, Port, and Stone (1972). The hitting time T_1 to state 1 is the minimum or first time greater than the starting time that the process visits state 1 again. Set $\rho_{11} = Pr(T_1 < \infty)$. Then,

$$\begin{aligned} \rho_{11} &= Pr(T_1 < \infty) = 1 - Pr(T_1 = \infty) \\ &= 1 - \sum_{n=1}^{\infty} \alpha p (1-p)^{n-1} \\ &= 1 - \alpha p \left[\frac{1}{1-(1-p)} \right] = 1 - \alpha. \end{aligned}$$

Thus, from Hoel et al. (1972, p.18), we have

$$Pr(N_1 = m) = \rho_{11}^{m-1}(1-\rho_{11}) = (1-\alpha)^{m-1}\alpha; \quad m \geq 1.$$

Note that N_1 has essentially a geometric distribution depending only on α. The expected number of tests to detection is

$$E(N_1) = \sum_{m=1}^{\infty} m\alpha(1-\alpha)^{m-1} = \frac{1}{\alpha} \tag{2}$$

and

$$Var(N_1) = \frac{1-\alpha}{\alpha^2}$$

by simple properties of geometric series. The n-step transition matrix is easily seen to be

$$P^n = \begin{bmatrix} p(1-\alpha)(1-\alpha p)^{n-1} & (1-p)(1-\alpha p)^{n-1} & 1-(1-\alpha p)^n \\ p(1-\alpha)(1-\alpha p)^{n-1} & (1-p)(1-\alpha p)^{n-1} & 1-(1-\alpha p)^n \\ 0 & 0 & 1 \end{bmatrix}$$

and again, from Hoel et al. (1972, p.15),

$$Pr(T \leq n) = 1-(1-\alpha p)^n; \quad n \geq 1.$$

From this we see that T also has a geometric distribution with mean and variance given by

$$\begin{aligned} E(T) &= \frac{1}{\alpha p}, \\ Var(T) &= \frac{1-\alpha p}{(\alpha p)^2}. \end{aligned} \tag{3}$$

Using similar arguments, the distribution of N_2 can be established. In particular,

$$Pr(N_2 = m) = (1 - \frac{\alpha p}{1 - p + \alpha p})^m \frac{\alpha p}{1 - p + \alpha p}; \quad m \geq 0.$$

$$E(N_2) = \frac{1 - p}{\alpha p},$$

$$Var(N_2) = \frac{(1 - p)(1 - p + \alpha p)}{(\alpha p)^2}.$$

Finally, it will be convenient to mention that for nonusers ($\alpha = 0$) the above process reduces to a sequence of independent and identically distributed (i.i.d.) Bernoulli random variables where the number of tests over any time period has a binomial distribution. Hence, if Y is the number of tests in a month per person, we have

$$Pr(Y = k) = \binom{30}{k} p^k (1 - p)^{30-k}; \quad k = 0, 1, \ldots, 30.$$

The average number of tests is $E(Y) = 30p$, which can be multiplied by cost per test to yield an average monthly cost per person. For a 10% (20%) per month program, the daily testing rate is $p = .1/30 = .0033$ (.0066).

Probabilities of a Positive Test

In this section we develop the conditional probability α of testing positive as a function of the number of days per week cocaine is used. We need some results developed earlier.

Table 1 reproduces results from Thompson and Boyle (1994). The assumptions underlying Table 1 are:

1. A dose of cocaine is ingested at 10:00 p.m. in the evening.

2. The dose is a random variable following a distribution estimated from data obtained from the San Diego Navy Drug Screening Laboratory.

3. Cocaine wear-off or elimination from the body follows first-order kinetics as developed by Gibaldi and Perrier (1982) and Ambre (1985).

4. Urinalysis testing occurs at 10:00 a.m.

For example, Table 1 reveals that an individual taking cocaine Monday night will, if tested Tuesday morning, test positive with probability .9376. If tested Wednesday morning, the probability of a positive test decreases to .6508. By Friday morning there is no chance of a positive test.

Table 1

Probabilities of Testing Positive for Cocaine Use 1 to 7 Days After Ingestion

Day	t (hours)	$\alpha\ (t)$
1	12	.9376
2	36	.6508
3	60	.1229
4	84	0
5	108	0
6	132	0
7	156	0

Table 2 lists wear-off probabilities in a weekly cycle for all possible usage patterns for a 2-day per week cocaine user. For example, if cocaine is used Sunday and Monday, then the probability of a positive test on Monday is .94 (.9376 rounded to two places), and probabilities wear off according to Table 1 for the remainder of the week. Note that Table 2 assumes that cocaine has no cumulative effect. The process implied by Table 1 starts anew each day the drug is used. The last column of Table 2 records the simple average of the wear-off probabilities. The grand average is the simple average of the entries in the last column (or the average of all entries in the table). Thus, the overall α-level for a 2-day per week cocaine user is .45. Similar calculations associated with higher usage levels are summarized in the second column of Table 3. The last column of Table 3 gives the values of a quadratic fit to the values in the second column using restricted least squares. The restrictions are $\alpha(0) = 0$ and $\alpha(7) = .94$. The quadratic function is given by Equation 4.

$$\alpha(N) = .2527\ N - .0170\ N^2; \quad 0 \leq N \leq 7. \tag{4}$$

Figure 1 displays the quadratic fit. Using this continuous function defines α-levels at nondiscrete values of N. Hence, we can also speak of the probability of testing positive for any noninteger value between 0 and 7. This quadratic function will be important in determining deterrence functions as defined in the next section.

Table 2

Wear-off Probabilities: Two Days per Week Cocaine User

	Day of the Week							
Days Used	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Avg
Sun-Mon	0	.94	.94	.65	.12	0	0	.38
Sun-Tue	0	.94	.65	.94	.65	.12	0	.47
Sun-Wed	0	.94	.65	.12	.94	.65	.12	.49
Sun-Thu	.12	.94	.65	.12	0	.94	.65	.49
Sun-Fri	.65	.94	.65	.12	0	0	.94	.47
Sun-Sat	.94	.94	.65	.12	0	0	0	.38
Mon-Tue	0	0	.94	.94	.65	.12	0	.38
Mon-Wed	0	0	.94	.65	.94	.65	.12	.47
Mon-Thu	.12	0	.94	.65	.12	.94	.65	.49
Mon-Fri	.65	.12	.94	.65	.12	0	.94	.49
Mon-Sat	.94	.65	.94	.65	.12	0	0	.47
Tue-Wed	0	0	0	.94	.94	.65	.12	.38
Tue-Thu	.12	0	0	.94	.65	.94	.65	.47
Tue-Fri	.65	.12	0	.94	.65	.12	.94	.49
Tue-Sat	.94	.65	.12	.94	.65	.12	0	.49
Wed-Thu	.12	0	0	0	.94	.94	.65	.38
Wed-Fri	.65	.12	0	0	.94	.65	.94	.47
Wed-Sat	.94	.65	.12	0	.94	.65	.12	.49
Thu-Fri	.65	.12	0	0	0	.94	.94	.38
Thu-Sat	.94	.65	.12	0	0	.94	.65	.47
Fri-Sat	.94	.65	.12	0	0	0	.94	.38
						Grand Avg =		.45

Table 3

Probability α for Testing Positive:
Cocaine Use 0 to 7 Days per Week

Days Used	Actual α	Fitted α
0	0	0
1	.24	.24
2	.45	.44
3	.61	.61
4	.74	.74
5	.83	.84
6	.90	.90
7	.94	.94

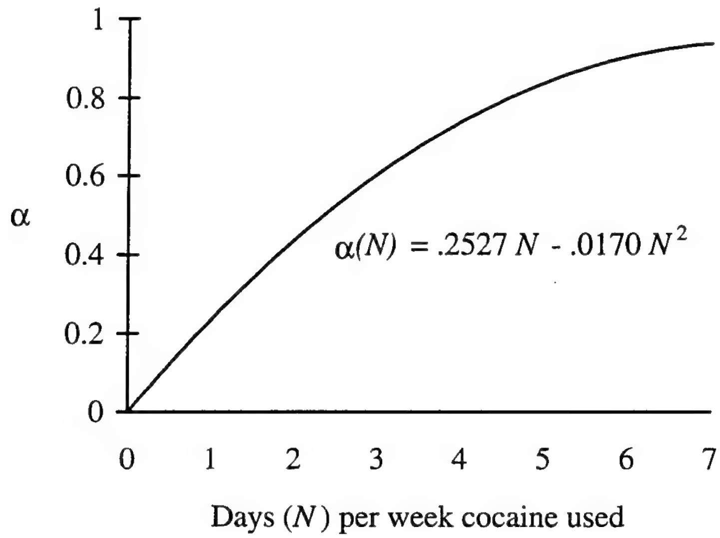

Figure 1. Probability of a positive test α given cocaine is used N days per week.

Deterrence Functions

The entries in Table 4 define four examples of demand functions for cocaine. An individual with demand function N_a uses cocaine 7 days per week when there is no threat of testing. All usage ceases ($\alpha = 0$) with any threat of testing. Thus, the average number of tests per month for any testing rate p is $30p$, the same as for nonusers. An individual with demand function N_b is a 7 days per week user of cocaine ($\alpha = .94$), no matter what testing rate is employed. Raising the testing rate decreases the average time to detection according to the first equation in Equation 3. The average number of tests to detection is constant at $1/.94 = 1.06$ according to Equation 2. Demand funtions N_c and N_d fall between the extremes N_a and N_b. N_c is convex to the origin and is a continuous version of N_a. As p increases from $p = 0$, demand drops off more rapidly for smaller values of p than for larger values of p. N_d is concave to the origin and is a continuous version of N_b. As p increases from $p = 0$, demand drops off more slowly for smaller values of p and more rapidly for larger values of p. Figure 2 graphs these two demand curves. We have chosen these two quadratic demand functions here simply for mathematical convenience. There is nothing special about them among the class of all possible continuous demand functions for cocaine. Note that one could reasonably hypothesize much more extreme versions of N_c and N_d. For example, one could speculate that a "rational" user of cocaine might cut usage to 1 or 2 days per week for small values of p in a neighborhood of $p = .005$, that is, a testing rate of 15% per month. An "irrational" user might continue to use every day until the testing rate approximates $p = 1$.

Table 4

Examples of Demand Functions for Cocaine

$N_a(p)=\begin{cases}7 & ;p=0\\ 0 & ;0<p\le 1\end{cases}$	$N_b(p)=7 \quad ;0\le p\le 1$
$N_c(p)=7(p-1)^2 \quad ;0\le p\le 1$	$N_d(p)=7(1-p^2) \quad ;0\le p\le 1$

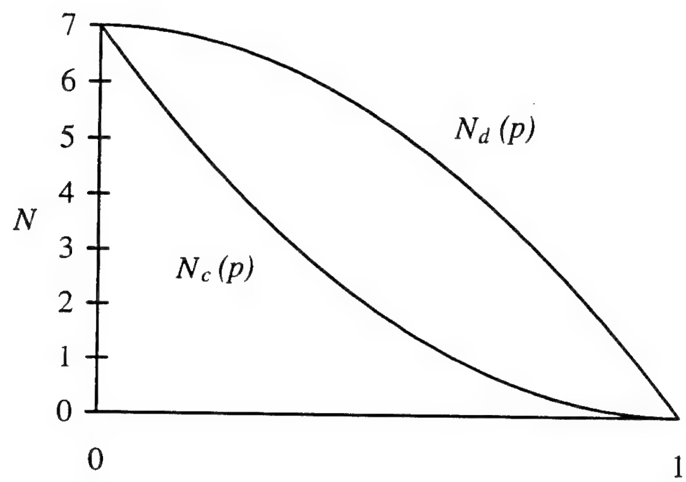

Figure 2. Number of days (N) per week cocaine is used as a function of the testing rate (p).

We define a deterrence function for cocaine usage as the composition of a demand function $N(p)$ and the function $\alpha(N)$ as defined by Equation 4. In general, deterrence functions are defined by

$$\alpha(p)=\alpha(N(p)). \tag{5}$$

In particular, we can use Equation 5 to determine the deterrence functions associated with N_c and N_d. These are, after some algebraic simplifications, the quartic expressions

$$\alpha_c(p)=.9359-.2058p-3.2291p^2+3.332p^3-.833p^4 \tag{6}$$

and

$$\alpha_d(p) = .9359 - .1029p^2 - .833p^4. \tag{7}$$

These two deterrence functions are graphed in Figure 3.

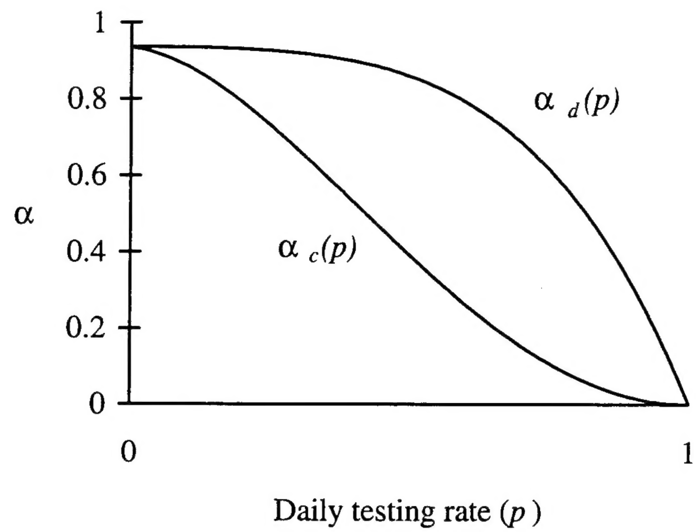

Figure 3. Examples of two deterrence functions.

Given a deterrence function $\alpha(p)$ defined by Equation 5, expressions for the average number of tests to detection and the average time to detection can be obtained by applying Equations 2 and 3. These are

$$N_1(p) = \frac{1}{\alpha(p)} \tag{8}$$

and

$$T(p) = \frac{1}{p\alpha(p)} \tag{9}$$

where the expectation operator has been dropped. For the specific deterrence functions defined by Equations 6 and 7, the average number of tests and average detection times given by Equations 8 and 9 are presented in Table 5 for the daily testing rates $p = .1$ to $p = .9$. For a decreasing deterrence function, the average number of tests must increase for increasing p. The average time to detection decreases to a minimum value at some testing rate p^* and increases for increasing values of p greater than p^*. For the example deterrence functions $\alpha_c(p)$ and $\alpha_d(p)$, the actual minimum values are $T_c(p_c^*) = 4.72$ days and $T_d(p_d^*) = 2.07$ days with $N_{1c}(p_c^*) = 1.84$ tests and $N_{1d}(p_d^*) = 1.37$ tests. The

optimal values of p are $p_c^* = .39$ and $p_d^* = .66$. These results were obtained using Newton's method.

Table 5

Average Number of Tests and Average Detection Times

p	$N_{1c}(p)$	$T_c(p)$	$N_{1d}(p)$	$T_d(p)$
.1	1.13	11.28	1.09	10.9
.2	1.26	6.32	1.13	5.67
.3	1.50	5.00	1.20	4.02
.4	1.89	4.73	1.31	3.28
.5	2.56	5.13	1.48	2.96
.6	3.82	6.37	1.74	2.90
.7	6.56	9.37	2.19	3.13
.8	14.40	18.01	3.12	3.90
.9	56.80	63.11	5.93	6.59

Again, we emphasize that the demand functions N_c and N_d are purely artificial. Data must be collected in order to estimate actual demand curves. One could speculate that for nonaddicted drug users, real world demand curves would decrease much more rapidly, leading to much smaller optimal p^*'s.

Discussion and Conclusions

A Markov daily testing model has been proposed with constant testing rate p and constant conditional probability α of a positive test. The distributions of all relevant random quantities and expected values were derived. Borrowing some results on cocaine kinetics from Thompson and Boyle (1994), α was modeled as a quadratic function $\alpha(N)$ of the number of days N per week that cocaine is used.

Various demand functions for cocaine were postulated. Here, a demand function for cocaine was defined as the number of days per week cocaine is used as a function of the testing rate, that is, $N = N(p)$. One extreme case is no change in N as p increases. In this case, the average number of tests to catch a cocaine user is constant and the time to detection decreases with increasing p. At the other extreme, demand drops to zero days per week for any positive testing rate. In this case, the number of tests in any time period follows a binomial distribution, just as for a nonuser. In general, deterrence functions were defined as $\alpha(p) = \alpha(N(p))$ for decreasing demand curves $N(p)$. These deterrence functions are decreasing in p. For these deterrence functions, the average number of tests to detection is increasing with increasing testing rates. The average time to detection decreases to a minimum and increases thereafter with increasing testing rates.

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